EE5907 Pattern Recognition
EE5027 Statistical Pattern Recognition

Robby Tan

Topics

- Robby Tan (EE5907 Part I + EE5027)
  - Contact: robby.tan@nus.edu.sg
  - Bayesian Inference
  - Linear Models for Regression and Classification
- Bai Soon (EE5907 Part II + EE5026)
  - LDA, SVM, PCA
  - Clustering and Applications
  - Deep learning

GA: EE5027 + First Half of EE5907

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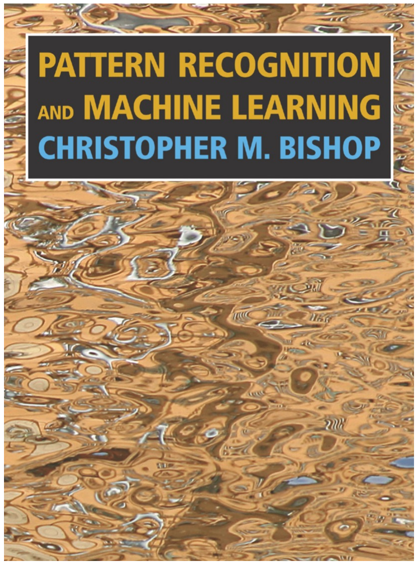
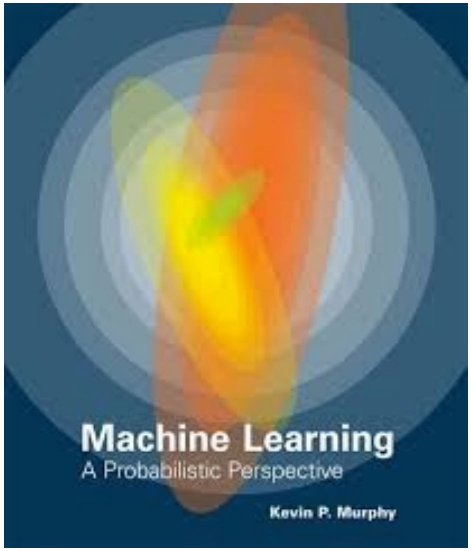
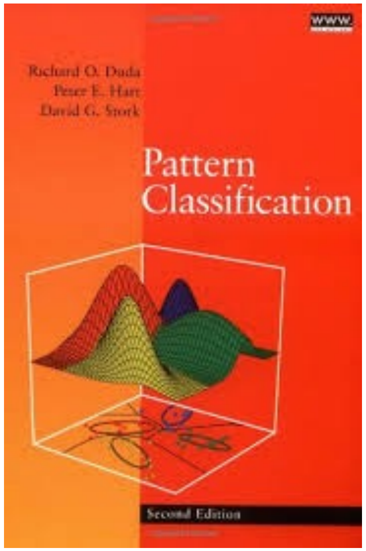
Read Manager

Email: e0927007@u.nus.edu

Main References







PRML -- free download : https://www.microsoft.com/en-us/research/people/cmbishop/prml-book/

Computer Vision: Models, learning and inference, Simon Prince, 2012
Free: www.computervisionmodels.com

Pre-requisites

- Pre-requisites
  - Probability, statistics, and linear algebra (vector spaces and matrix theory) as taught in typical undergraduate courses
  - Probability and statistics are <u>especially</u> important for first half of EE5907 + EE5027
  - Programming in Python (using Jupyter Notebook)
- <u>You will find this class very difficult if you don't have the pre-requisites</u>
- <u>If this is your first graduate class, you will also find it to be substantially more difficult than your undergrad courses</u>

State-of-the-Art

- EE5907/EE5027/EE5026 do NOT cover state-of-the-art. Teach concepts needed to understand state-of-the-art

- For state-of-the-art:
  - Conference papers: CVPR, ICCV, ECCV, ICML, ICLR, NeurIPS, etc
  - Journal articles: IJCV, T-IP, JMLR, T-PAMI, etc
  - EE6733: Advanced Topics on Vision and Machine Learning

- EE5934/EE6934: Deep Learning

LumiNUS and Website

- Lecture notes will be made available on the course website (the first part): https://tanrobby.github.io/teaching/ece_pattern_recognition/index.html
- Assignments are submitted via LumiNUS
- Deadlines are strict:
  - Late submission will be deducted 2 points (out of 10) for every 24 hours.

Assessments

- EE5907
  - 2 CAs (2 x 20%)
    - Individual projects (absolutely no copying permitted)
  - Final Exam (60%)
    - More information to come
- EE5027
  - 1 CA (40%) same as EE5907 CA1
  - Final exam (60%)
    - More information to come

Academic Integrity

Academic honesty is compulsory in finishing the assignments and the exams:

1. Exchanging codes is not allowed.
2. Using codes from the previous years or from the internet is prohibited, unless stated otherwise in the lectures.
3. Copying texts of the reports from other groups is strictly prohibited.
4. Generally, cheating, academic misconduct, plagiarism, and fabrication of any submitted material (including code and text) are not tolerated.

Any violation to the academic honesty will imply failure to pass the course.

Introduction

What is Artificial Intelligence (AI)?

- AI = intelligence displayed by machines
- Unsolved since 1950s
- Recent resurgence made possible by machine learning and deep learning

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  - Pattern Recognition: automatically detect patterns from data
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  - Google search
  - Driverless cars
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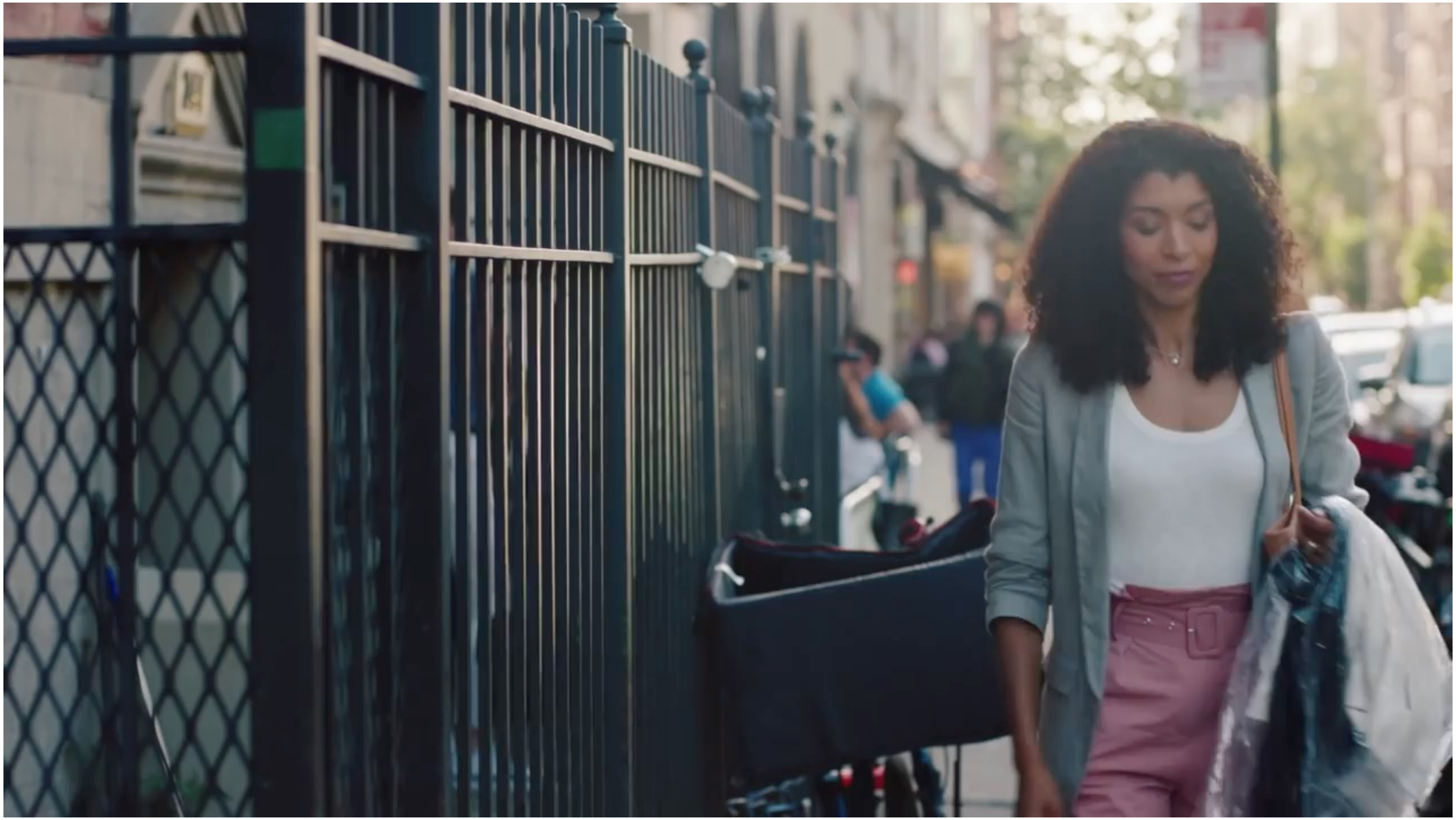
  - Driverless cars
  - Banking fraud detection
  - Detection and diagnosis of diseases
  - Biometric (e.g., fingerprint security)
  - DNA sequence identification (e.g., Counsyl)
  - Manufacturing (e.g., machine vision)

Google Assistant



Amazon Go

Types of Machine Learning

Supervised Learning

- Given input-output pairs $D = \{x_i, y_i\}_{i=1:N}$, learn mapping $y = f(x)$
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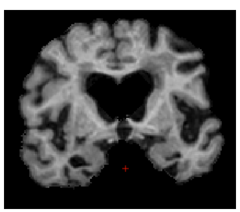
Training: Learn relationship between inputs (MRI) & target labels (AD or healthy)

Alzheimer's Disease (AD)



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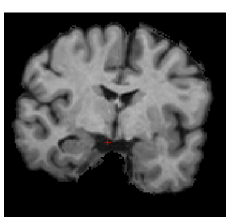
Healthy



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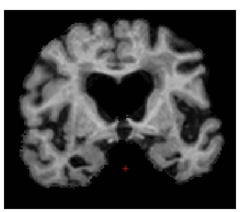

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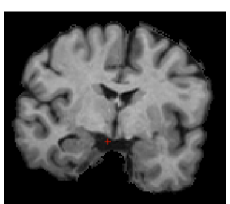

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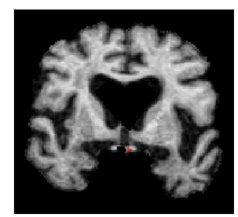
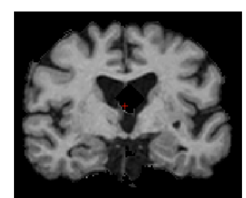
Testing: Given new MRI, Predict AD or healthy



Healthy or AD?



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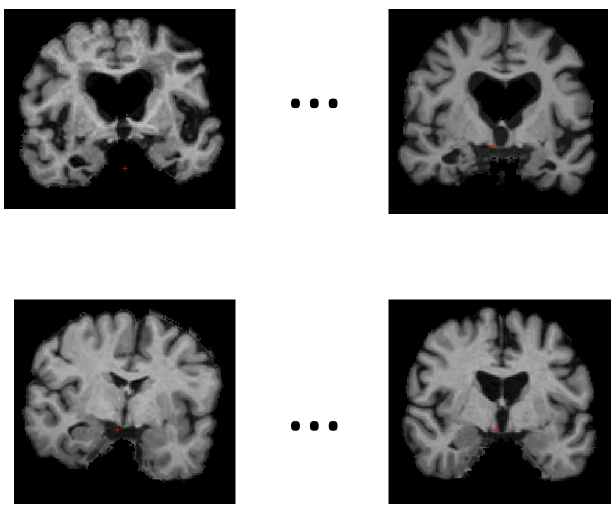

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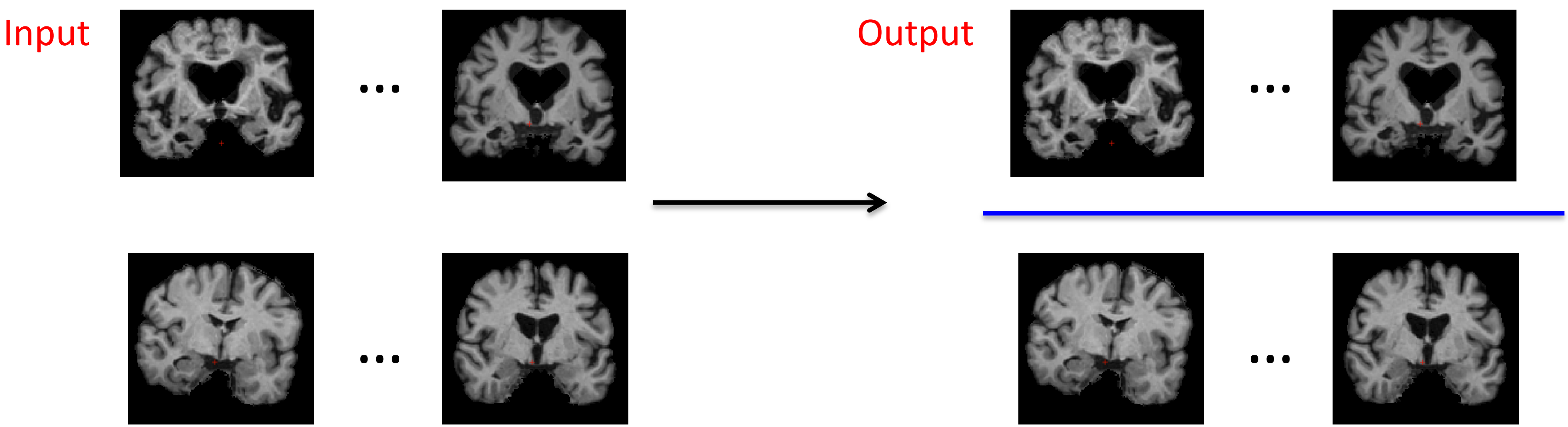

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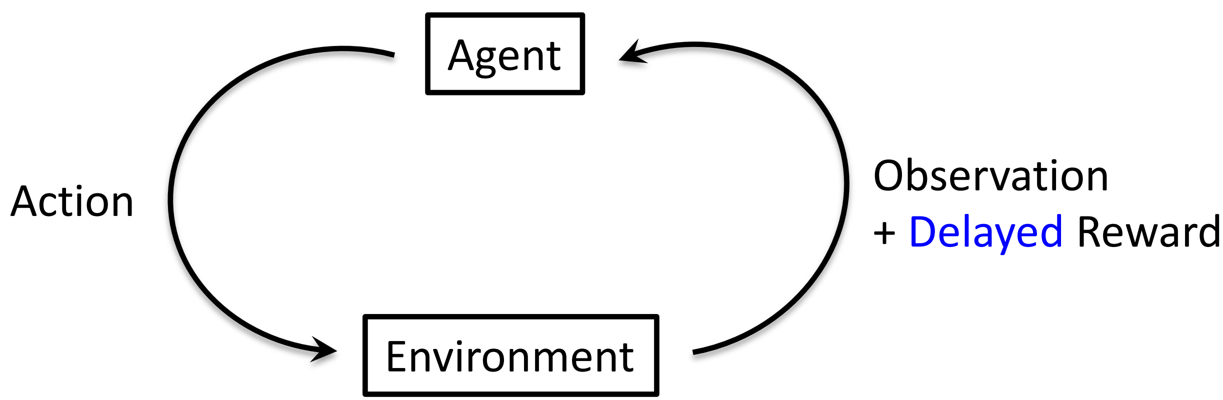
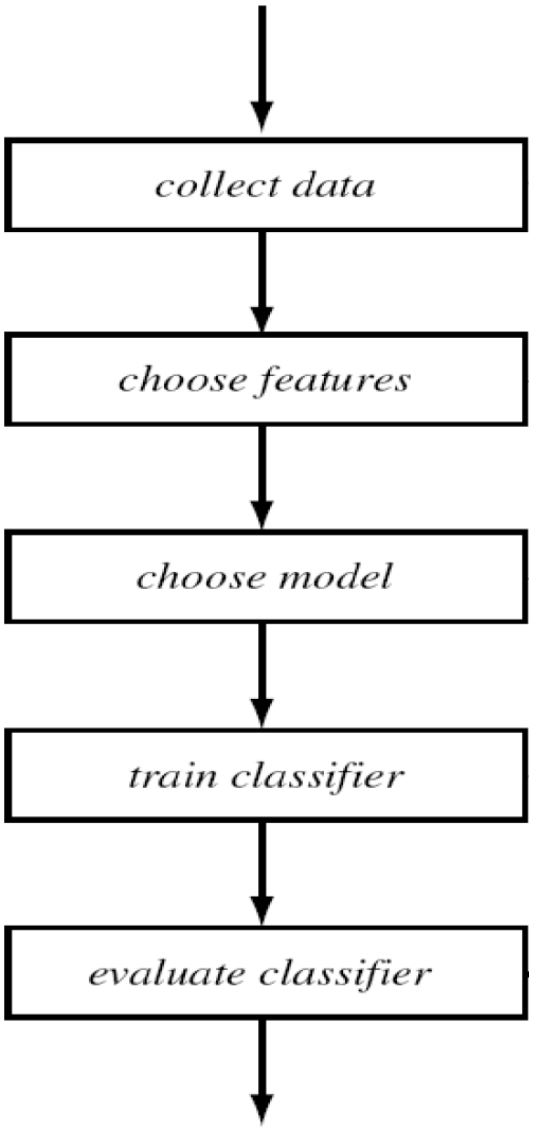
  - Reinforcement learning: learn actions by trial & error



Questions?

Some Background Knowledge in Machine Learning

Design Cycle For Supervised Learning



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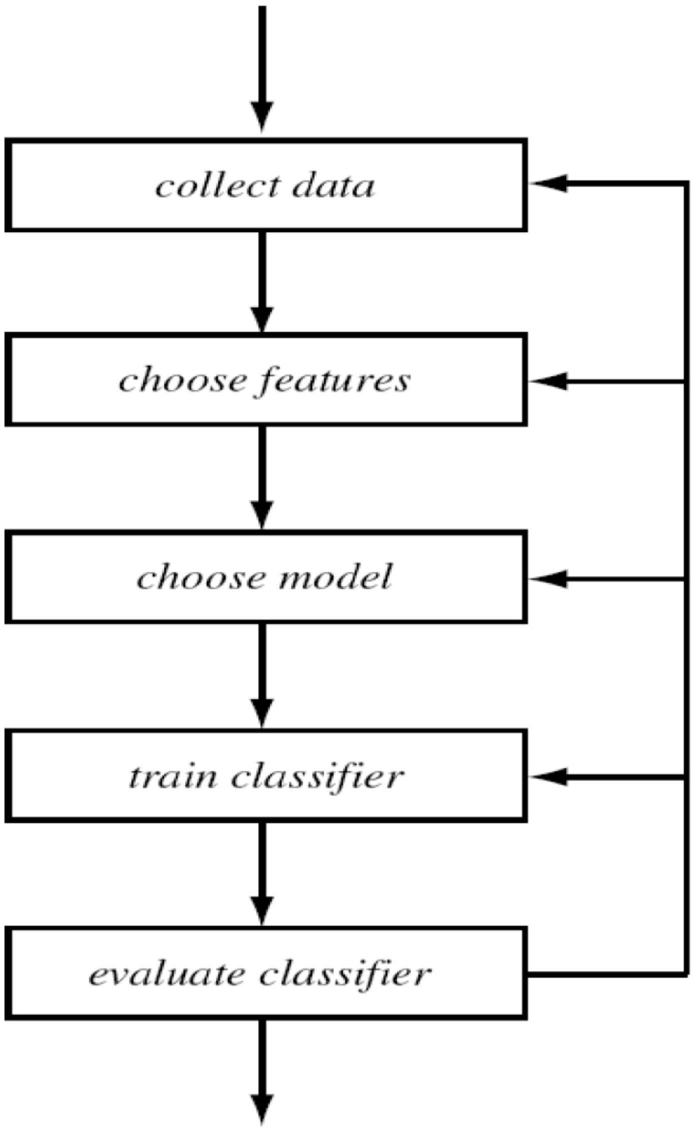
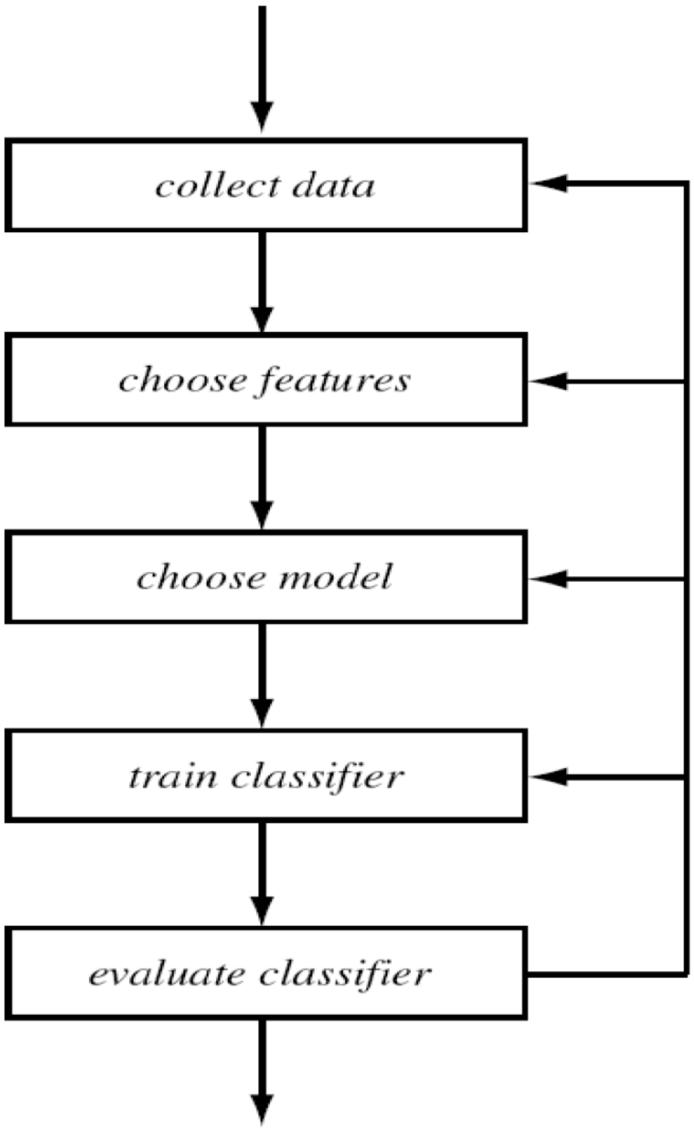
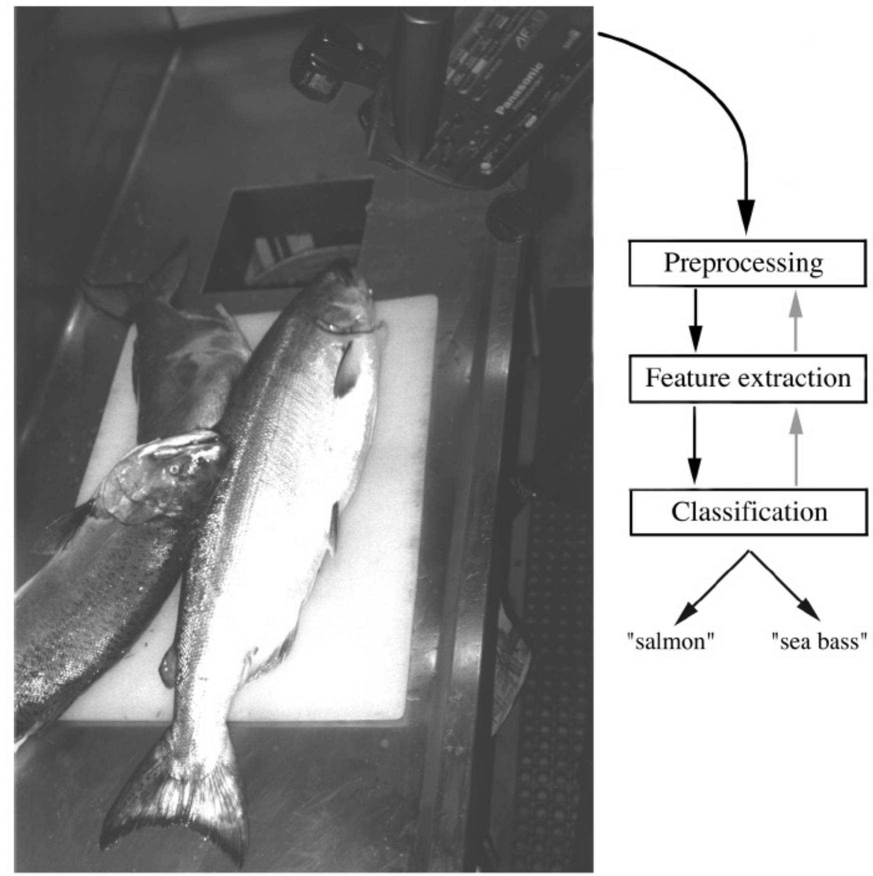


Design Cycle Example: Salmon vs Seabass





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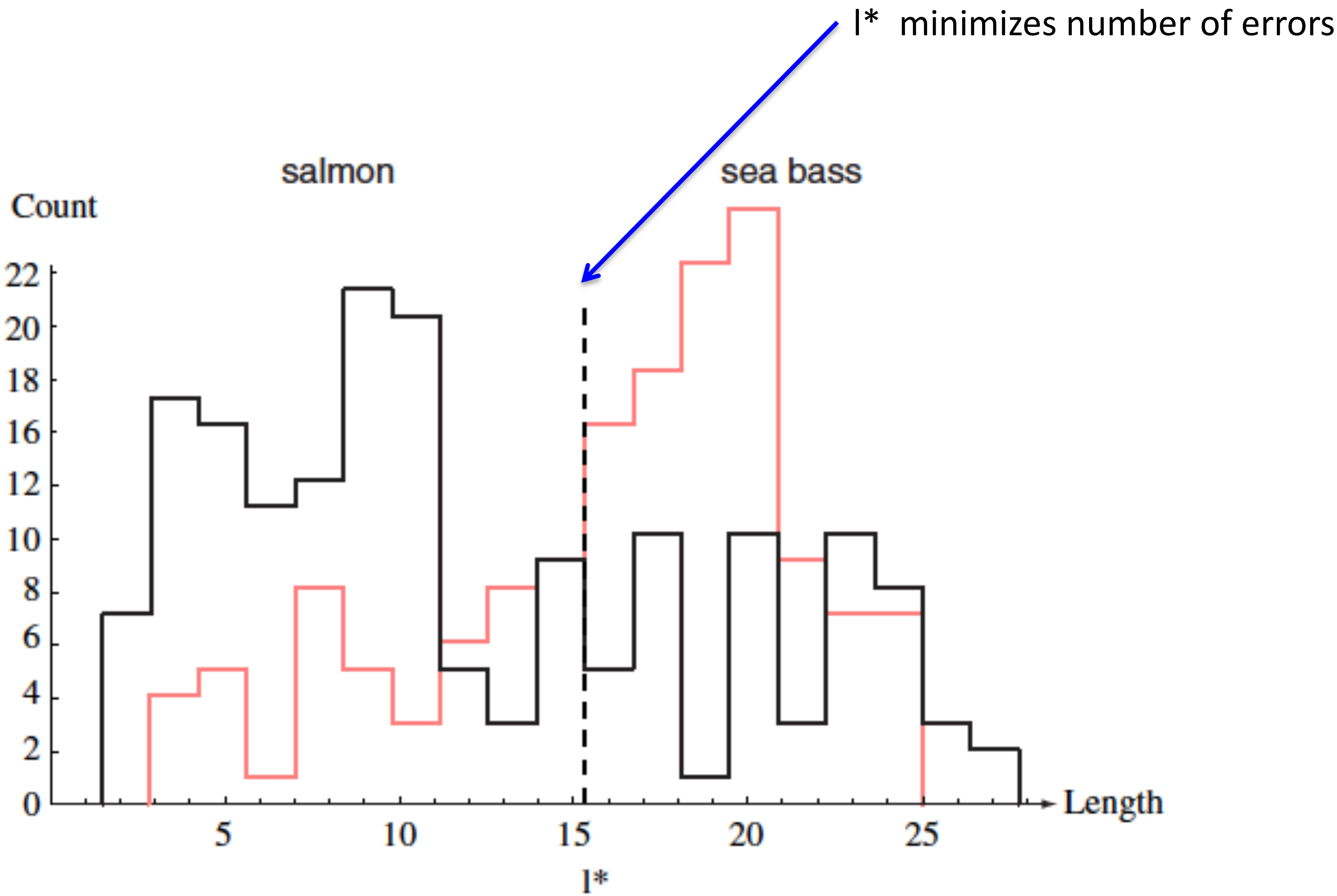
- Re-visit previous steps if performance unsatisfactory

Feature Engineering is Important!



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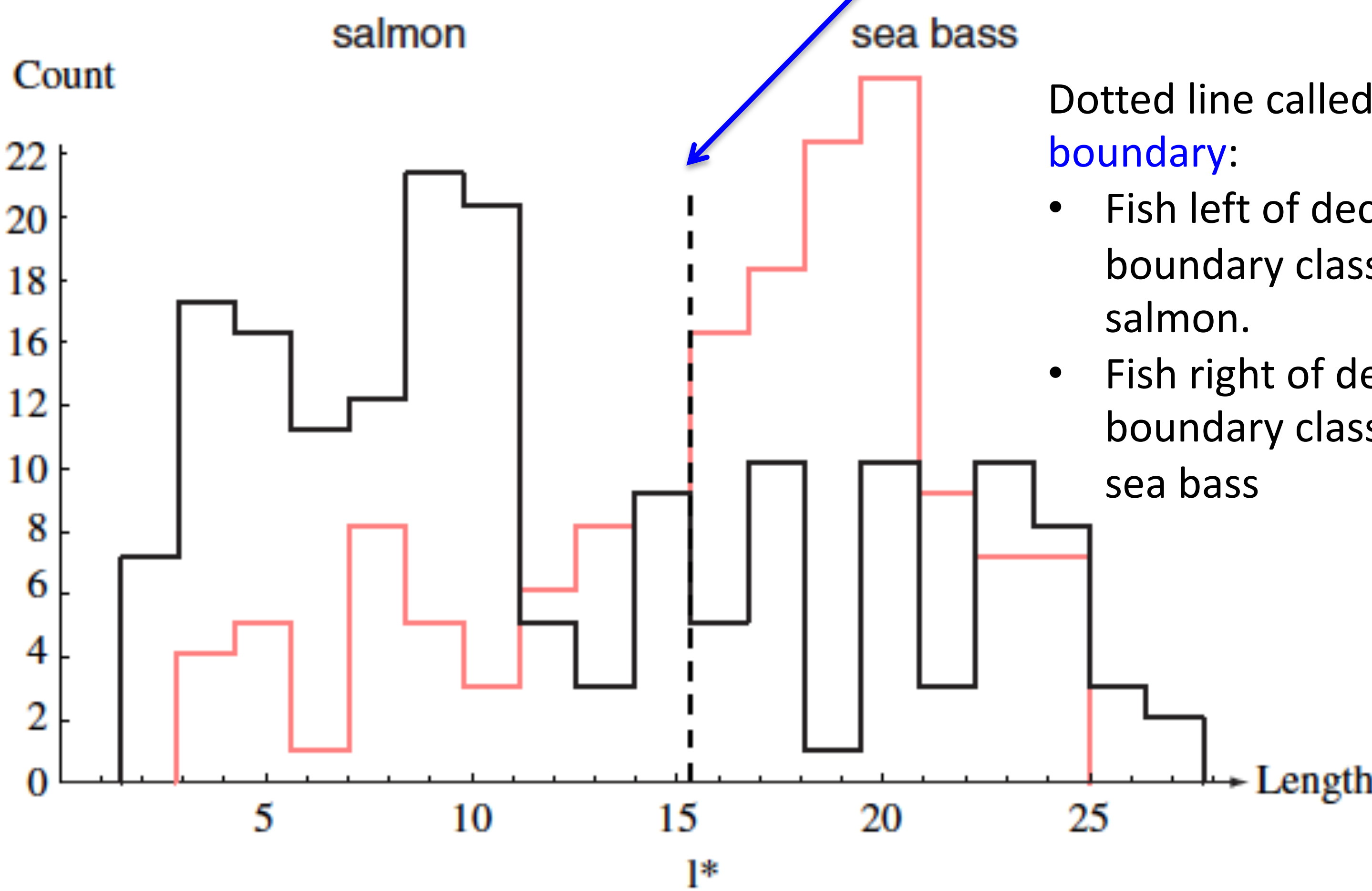

Dotted line called decision boundary:

- Fish left of decision boundary classified as salmon.
- Fish right of decision boundary classified as sea bass

Feature Engineering is Important!

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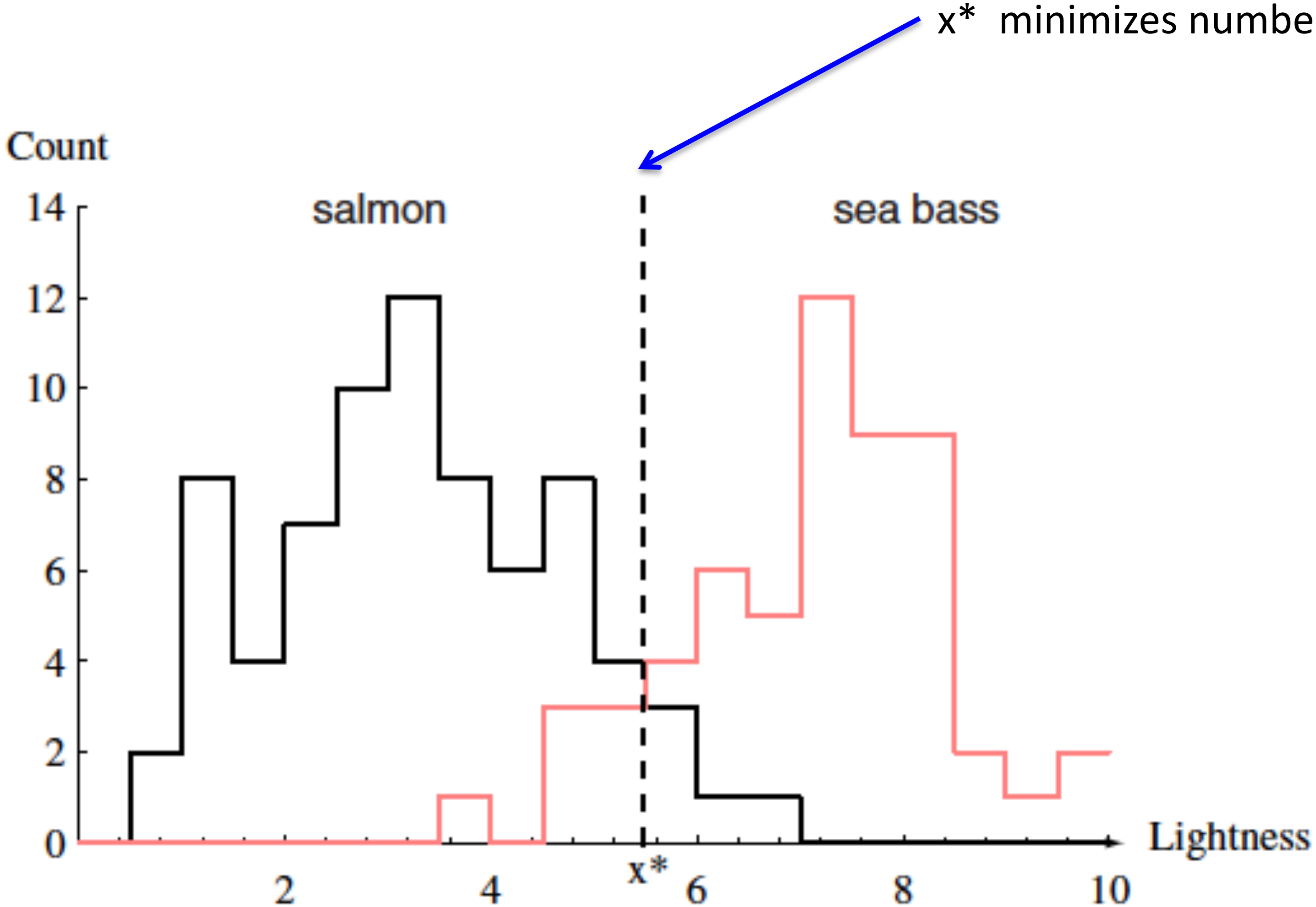
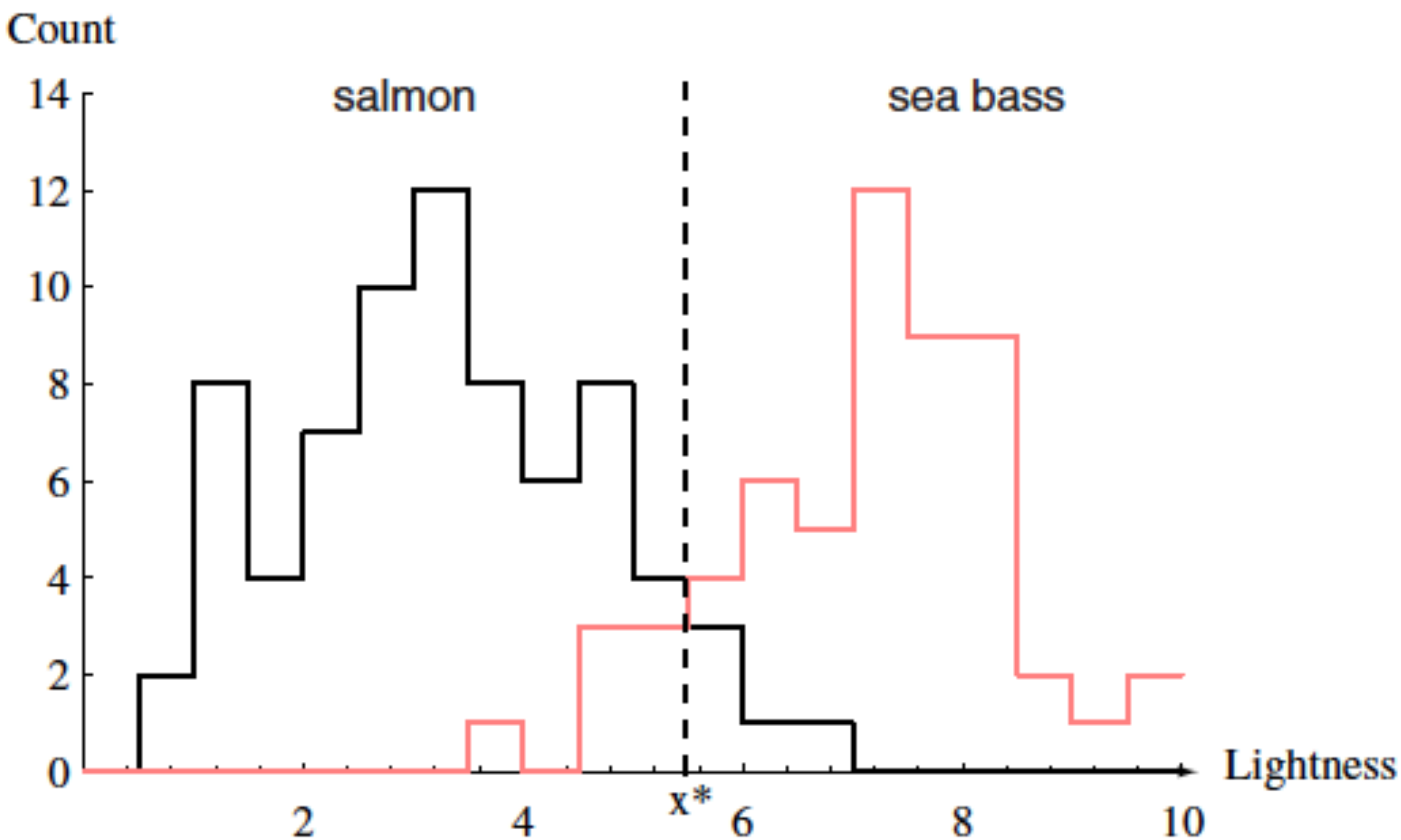


Decision Theory: Not All Errors are Equal

- Example: customers ok with finding salmon in cans marked as sea bass, but very upset to find sea bass in cans marked as salmon
  - Shift decision boundary to minimize angry customers



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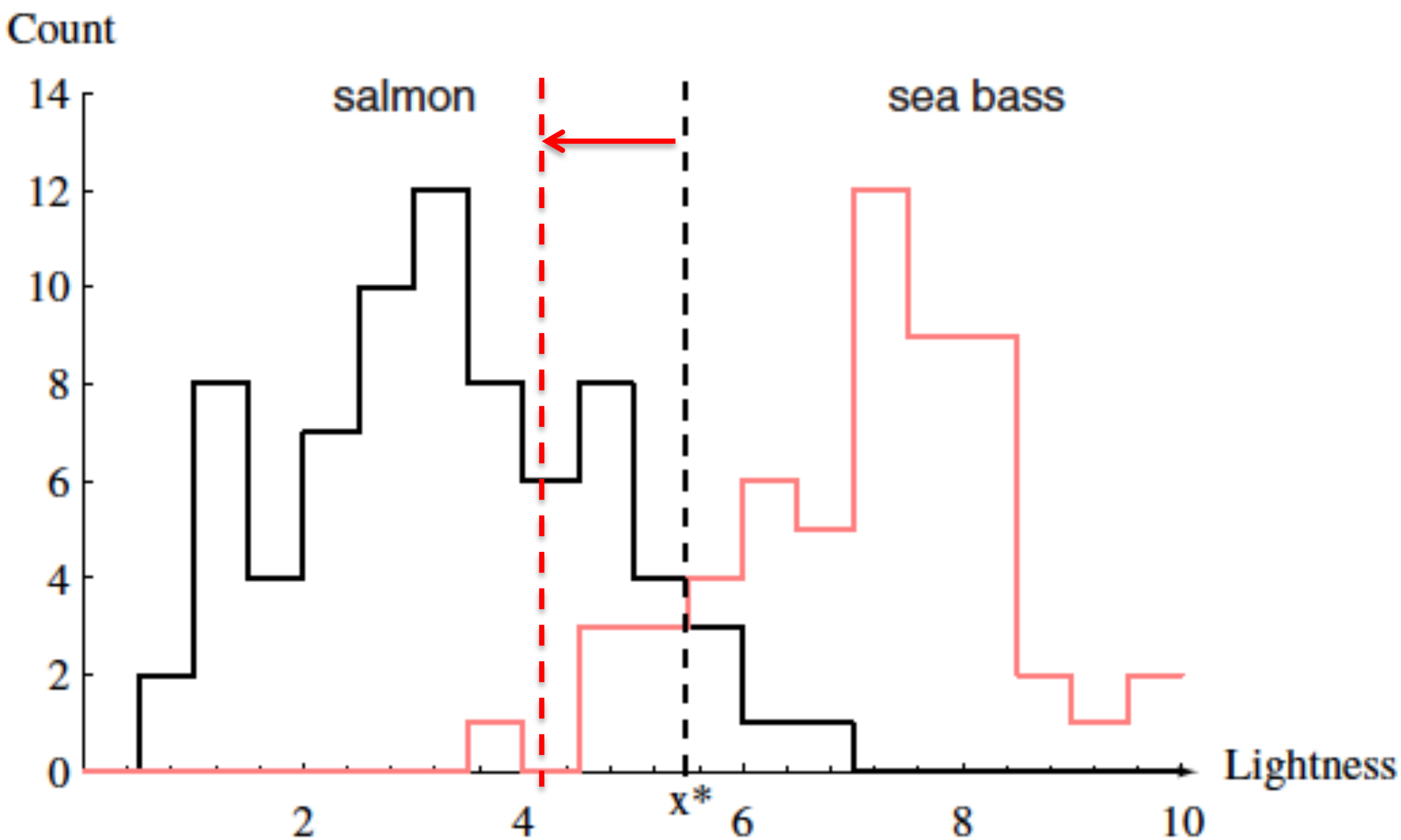
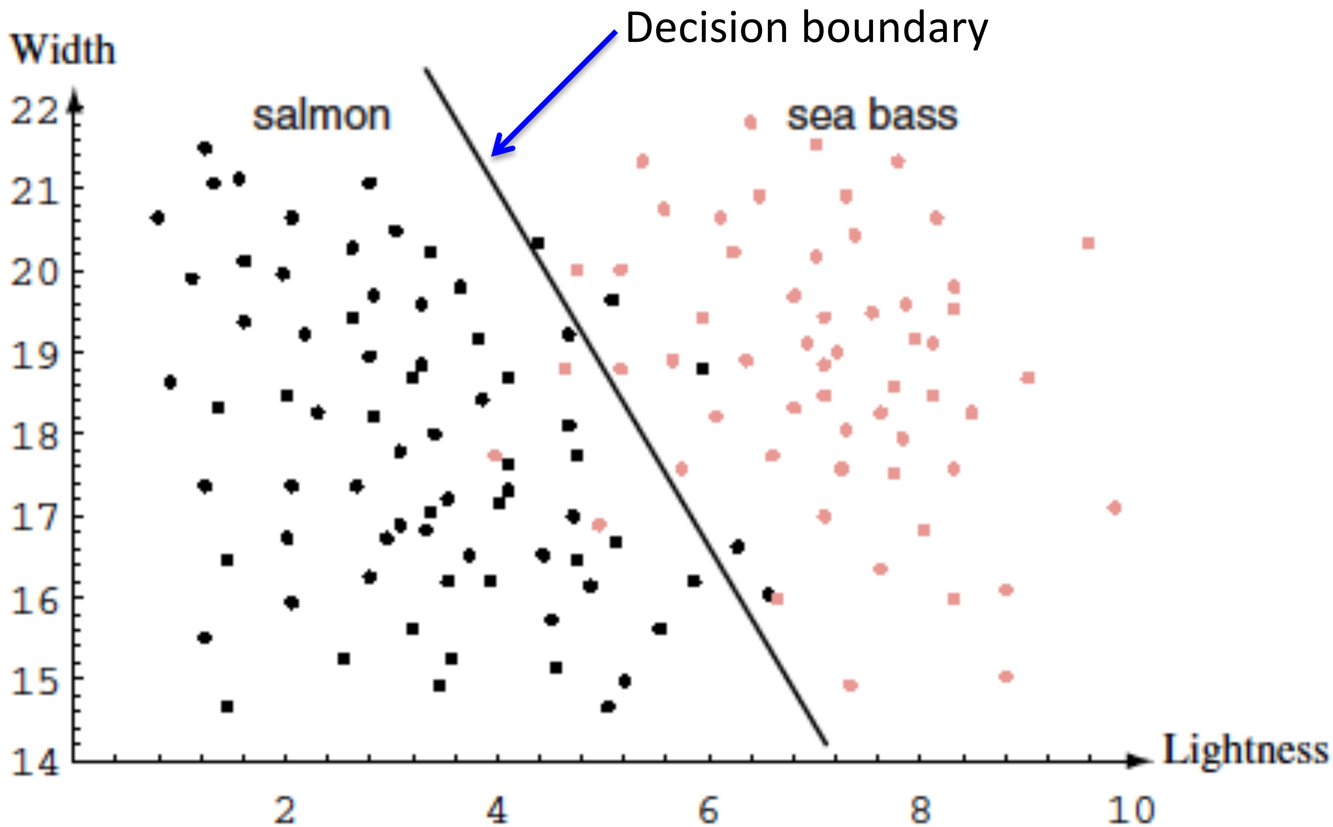


Curse of Dimensionality

- More features might improve performance, but some features (e.g., length) might be useless



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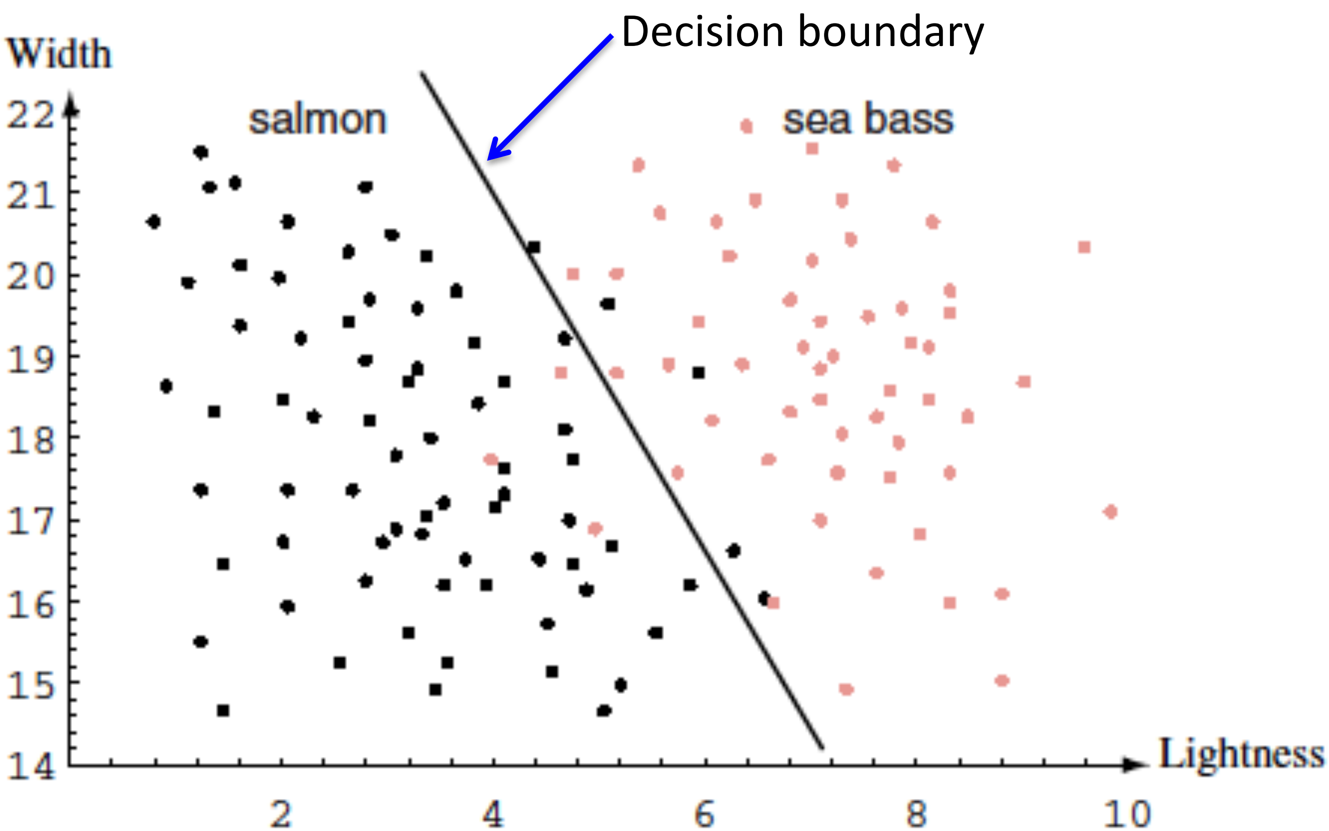
- Curse of dimensionality: too many features can lead to worse performance



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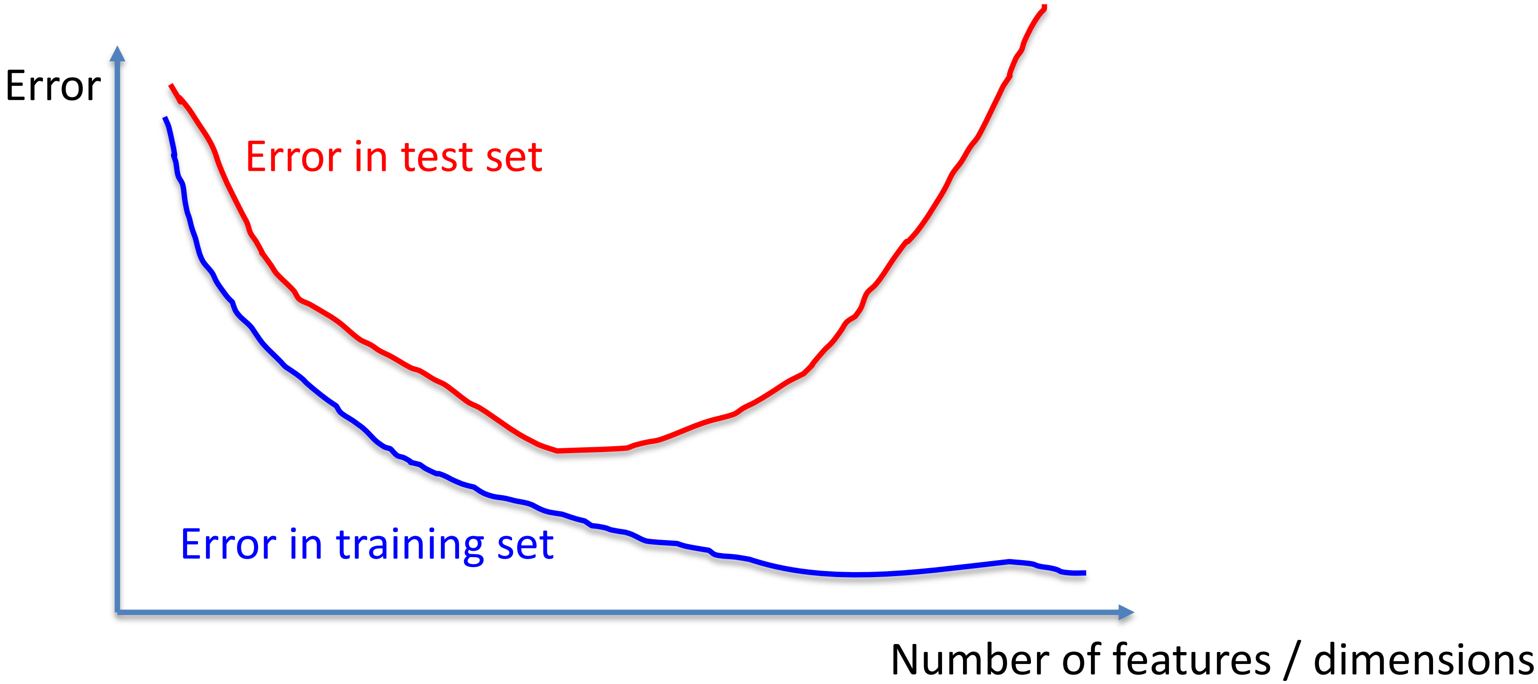

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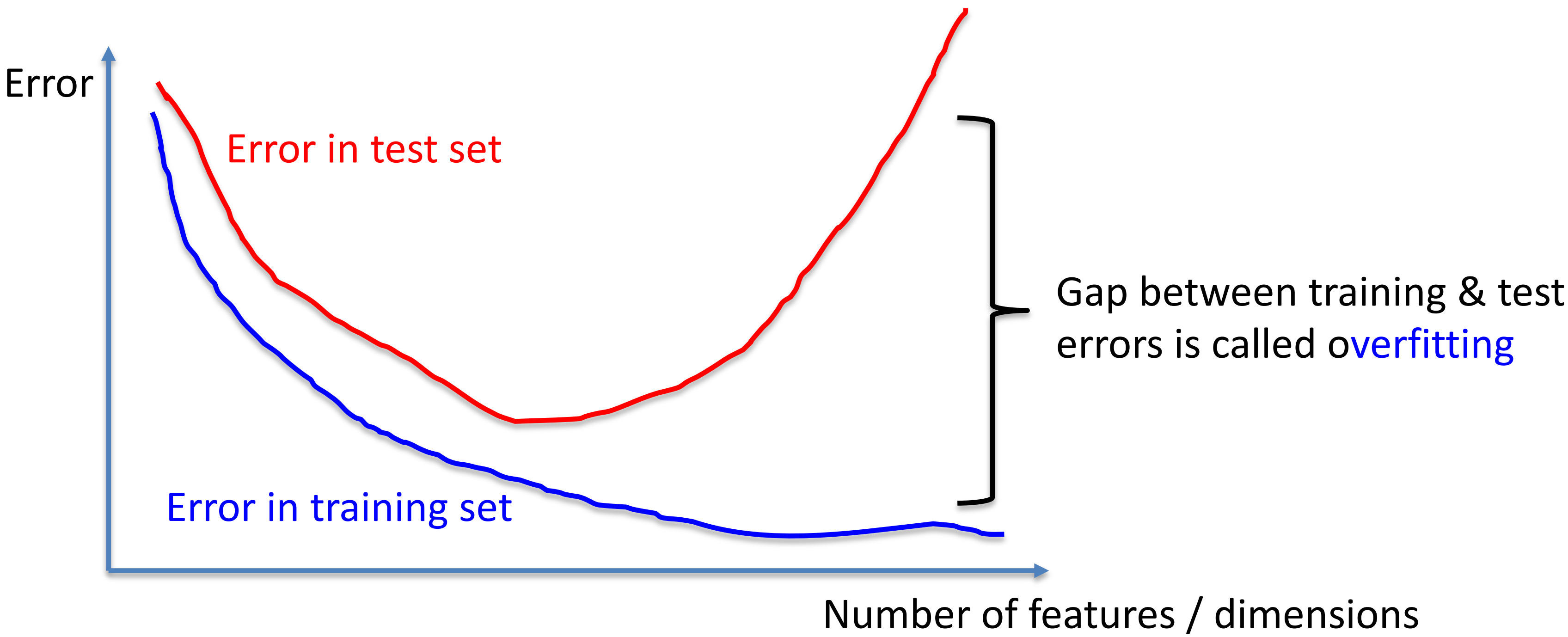
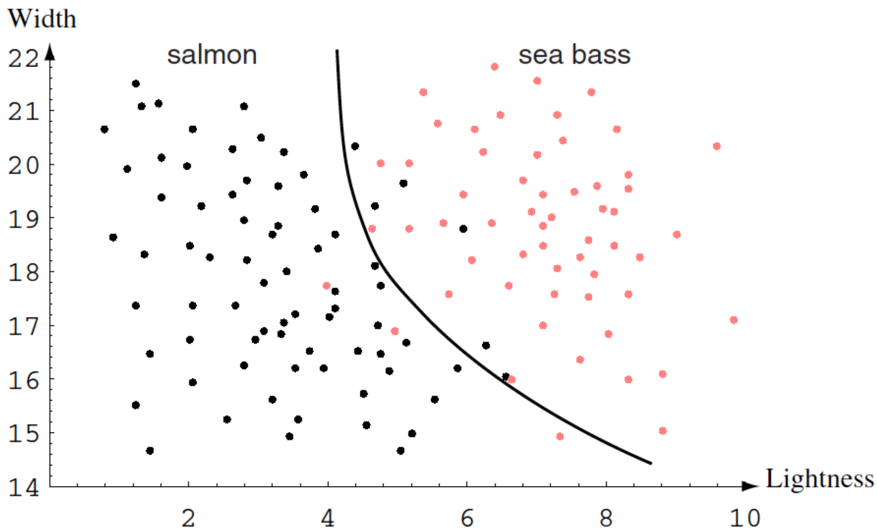


Model Complexity

- Instead of increasing the number of features, can also use more complex decision boundaries (models)
- This can potentially reduce errors, but might also increase errors



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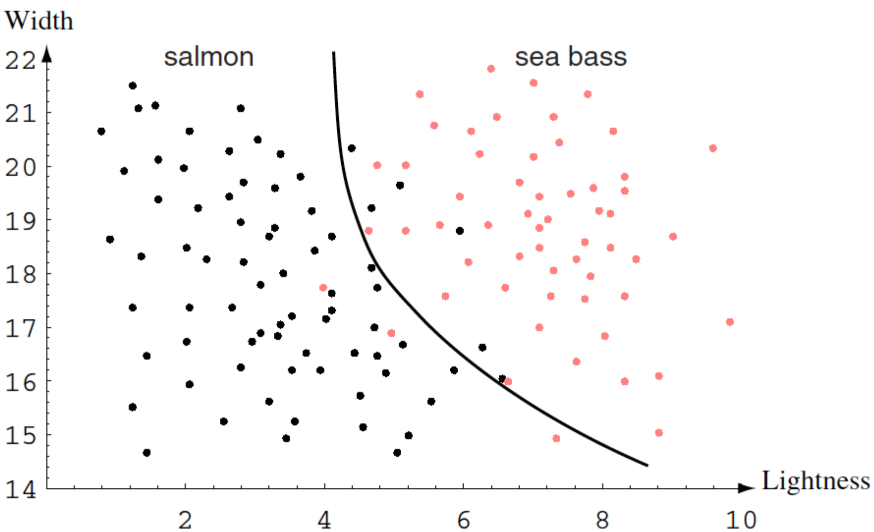

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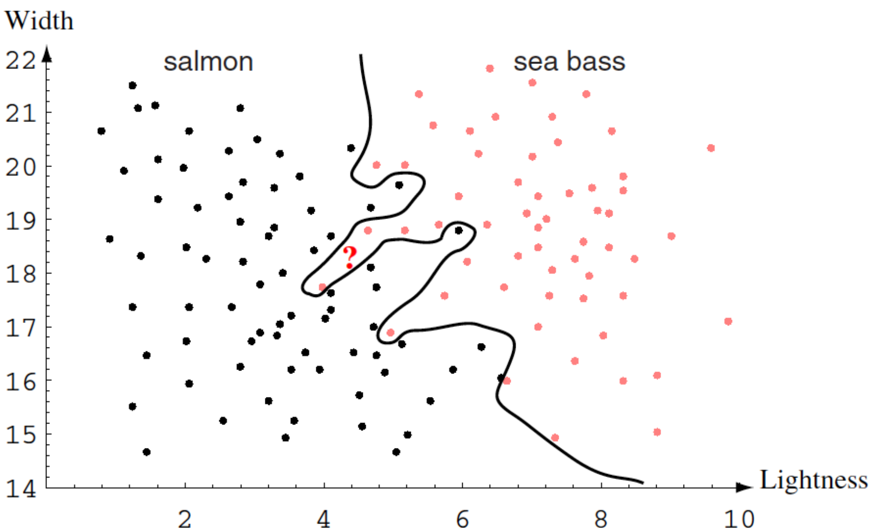

"?" likely to be salmon, but classified as sea bass

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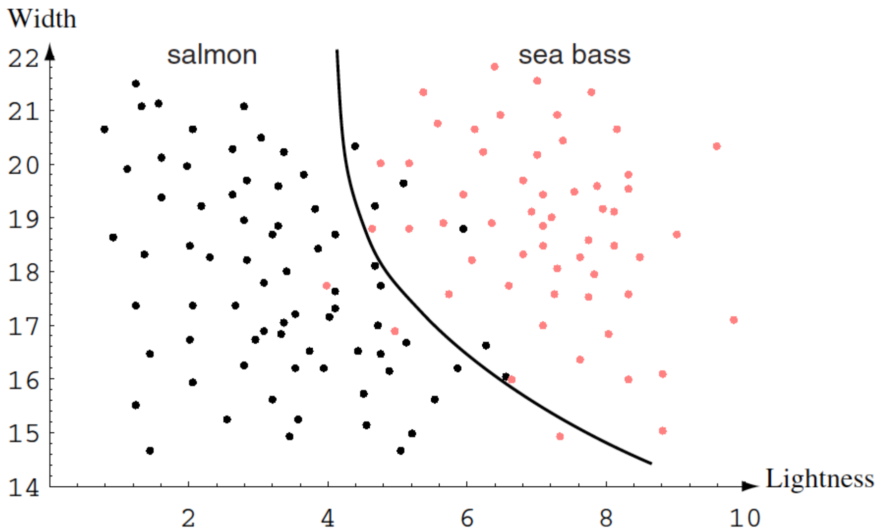
- Model complexity roughly related to # model parameters (e.g., quadratic decision boundary requires more parameters to specify than linear decision boundary)



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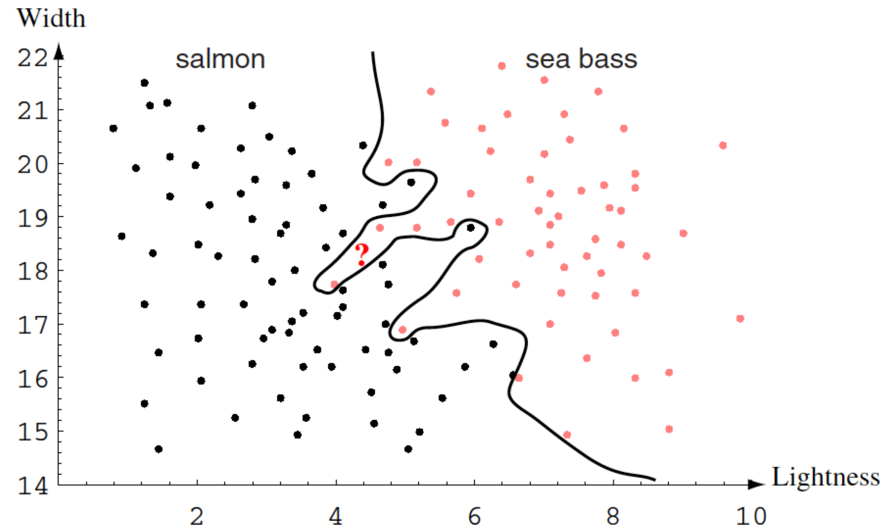

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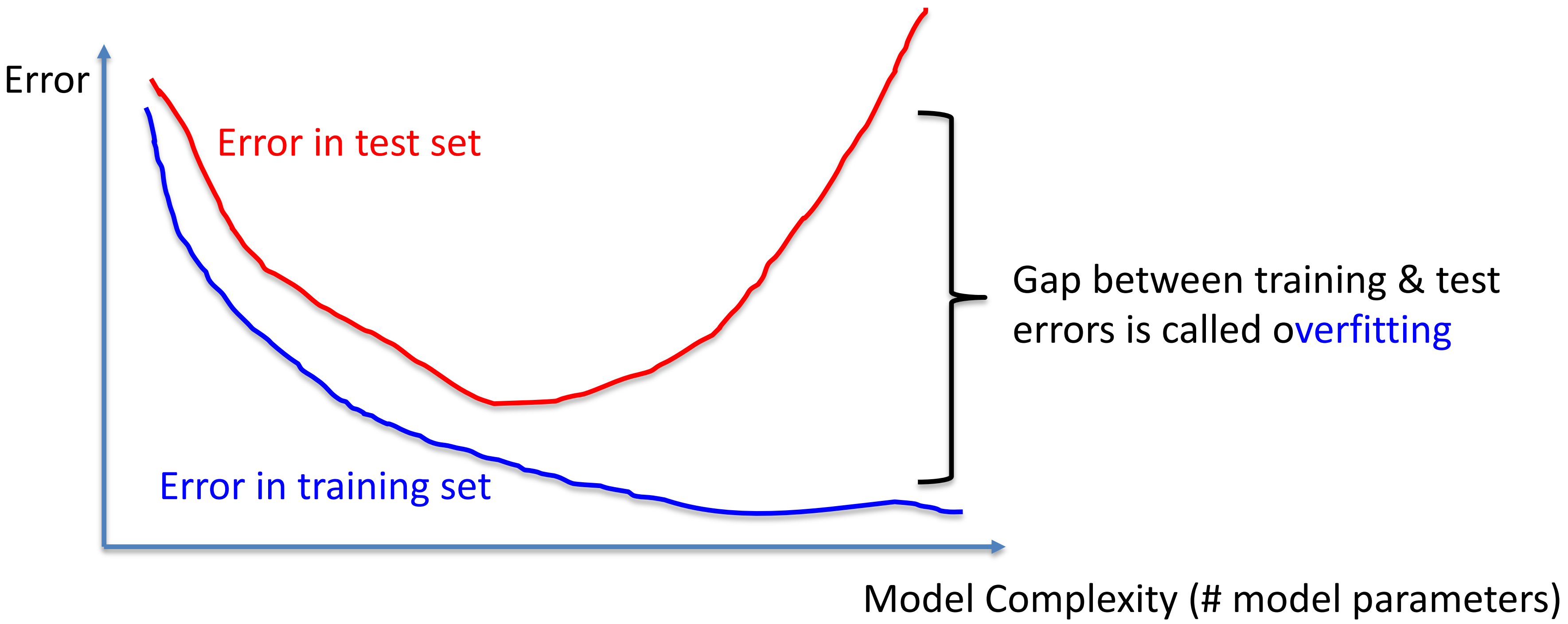

Training, Validation, Test Sets

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- However, splitting data into training-test set not enough
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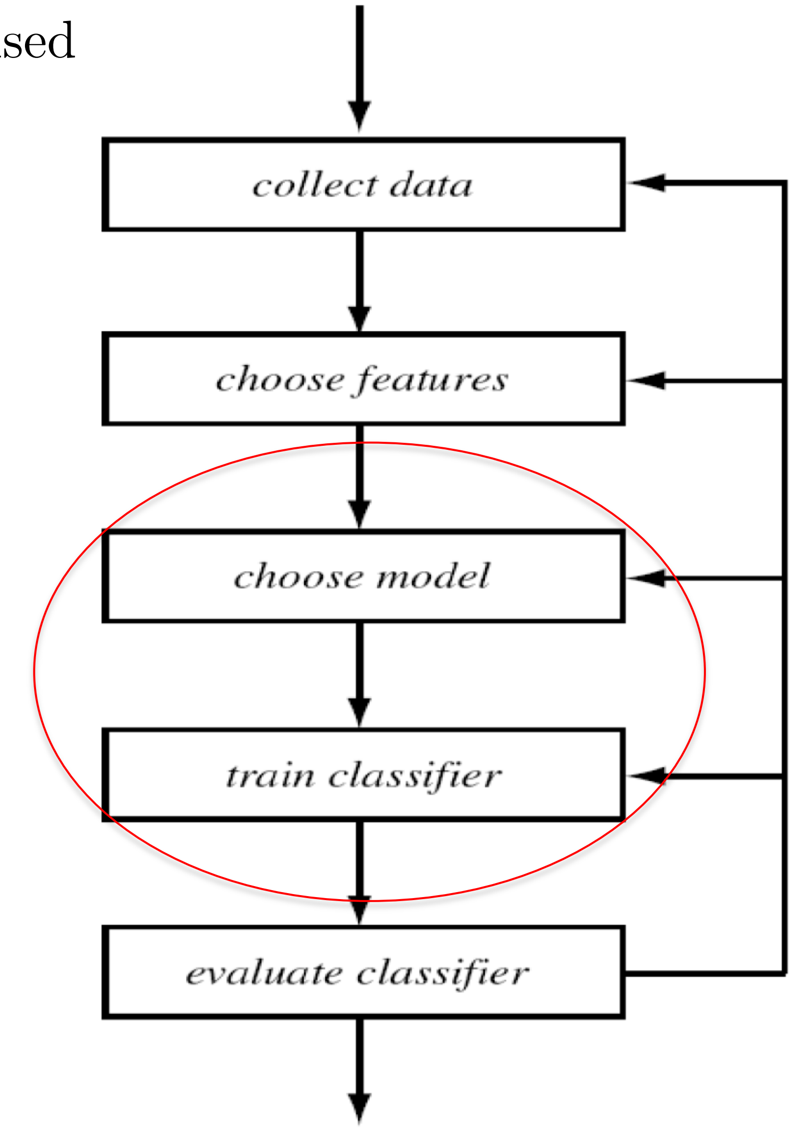
  - But we will have used the test set twice. If you repeat this many times, you will overfit to the test set
- Best practice: split data into training, validation and test sets
  - Train on training set & evaluate error on validation set
  - Repeat as many times as we like
  - Once satisfied with results, then apply to test set to get realistic error quantification

What will be covered?

- Focus on classification/regression/unsupervised learning
  - Assume features already extracted
  - Strong bias on probabilistic approaches



Why Not Just Teach Deep Learning?

- In certain settings, deep learning do not beat classical machine learning, e.g., logistic regression
  - These classical approaches can be significantly faster and easier to implement

Inpatient Mortality, AUROC[1](95% CI)	Hospital A	
Deep learning 24 hours after admission	**0.95**(0.94-0.96)	Deep learning
Full feature enhanced baseline at 24 hours after admission	0.93(0.92-0.95)	Logistic Regression

Google Research, Scalable and accurate deep learning with electronic health records, NPJ Digital Medicine, 2018

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Deep learning

Logistic Regression

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- Machine learning is cyclical
  - Our goal not to teach you only the popular stuff, but foundational knowledge useful regardless of what is popular because that will change

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- Curse of dimensionality, model complexity, overfitting
- Training-validation-testing

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